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Shaft Orbit Feature Based Rotator Early Unbalance Fault Identification

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Abstract

Feature extraction is crucial to rotating machinery prognosis, which is an important aspect of condition monitoring as well as maintenance program, since the quality of feature will impact the result significantly. Vibration signals are commonly used as the source for feature extraction during the prognosis process, especially the energy feature of fundamental frequency (which is written as 1X), 2X, 3X, 1/2X, etc. Yet this kind of feature shows insufficiency for identifying stages of performance degradation and classifying the type of early fault, therefore researchers focused mainly on improving the methods of feature extraction to solve this problem. However, features extracted from vibration signals always ignore some fault information such as kinematics information and phase information, thus other source of feature is needed to provide supplement or even substitute for higher efficiency and sharpness of separation in rotating machinery prognosis, which are strongly demanded by today's complex and advanced machines. This paper introduced one kind of classic feature source: shaft orbit, which is widely used in traditional diagnosis for failure classification, into prognosis, and its effectiveness is verified in rotor early unbalance fault identification using features extracted from it, compared with energy features of frequency band extracted from vibration signals. Result shows that shaft orbit feature can be used in identifying different early fault stages of rotor unbalance, which indicates that utilizing shaft orbit as source of feature extraction can provide a new approach of getting early fault features in rotating machinery prognosis.

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Keywords: Prognosis, Feature, Shaft orbit, Early fault, Rotating machinery

1. Introduction

Feature extraction is a crucial process in rotating machinery fault prognosis and is probably one of the most challenging ones. If the features are not potent enough, the prognosis result may not be satisfying or even turn out to be invalid, even if every process after feature extraction such as feature selection and fault identification is robust and valid. What is more, the variety of features should be enough so that there is possibility that their combination can create a potent feature. Yet in rotating machinery prognosis, vibration signal is almost the only feature source for feature extraction, as is discussed by Vachtsevanos et al.[1], differences among features always depend on the different feature extraction methods, such as time domain analysis, frequency domain analysis, time-frequency domain analysis, as is reviewed by Jardine et al.[2] and Heng et al.[3]. However, due to some inherent shortages in vibration signal, such as neglect of phase information and lack of kinematics information, features extracted from vibration signal have come to bottleneck in rotating machinery prognosis for identifying and classifying early fault of rotating machinery. Therefore, other feature source is demanded to provide supplement or even replace vibration signal under some circumstances. Shaft orbit feature is widely used for classification the existing failure in rotating machinery diagnosis. Considerable efforts have been made to develop methods of purification, feature extraction and application of shaft orbit for classifying the types of malfunction or failure of rotating machinery was proved to be effective, as is discussed by Qu et al.[4], Shi et al.[5], Xiang et al.[6], Peng et al.[7], and Voulgaris et al.[8]. Research of tools which could help to improve the quality of feature extracted, the accuracy of prediction and classification such as wavelet packet decomposition (WPT), principle component analysis (PCA), logistic regression (LR) [9], Support vector machine (SVM) [10], etc. are also developed and applied.

This paper presents the utilization of features extracted from shaft orbit to identify early fault of unbalanced rotor and

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compared the results with those utilizing features extracted from vibration signal. The organization of the rest of the article is as follows. The shaft orbit feature definition and extraction method are presented in Section 2, in which approaches to verify the effectiveness of shaft orbit features in identifying early fault are also summarized; experiments and results are presented in Section 3; conclusions are given in Section 4.

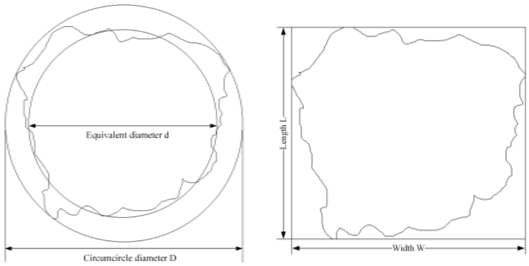
2. Methodology

The shaft orbit features used in this research are relatively simple in concept, including closeness and abundance, which are parameters with geometric significance. The mathematical definition of closeness and abundance can be shown as Fig.1. Closeness, which is defined as the ratio between the equivalent diameter (marked as “d”) and circumcircle diameter (marked as “D”) of the graphics of shaft orbit, as shown in Fig.1(a), is a dimensionless parameter used to describe and characterize discreteness of the graphics of shaft orbit. Abundance, defined as the ratio between the vertical length (marked as “L”) and horizontal width (marked as “W”) of the graphics of shaft orbit, as is shown in Fig.1(b), is also a dimensionless parameter and can be used to describe the corresponding deformation of shaft orbit to some extent when fault occurs.

Energy features of frequency spectrum, used as comparison in this research, are extracted from vibration signals using wavelet packet decomposition (WPT). WPT is originally known as Optimal Sub-band Tree Structuring (SB-TS), sometimes known as just Wavelet Packets or Sub-band Tree, is a wavelet transform where the discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform [11].

The dimensionality of the extracted features is reduced utilizing principle component analysis (PCA). PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components[12]. Thus the major fault information (above 90%) is kept and meanwhile the dimensionality of feature space is the same with shaft orbit feature which make the comparison more dependable.

Support vector machine (SVM) is used as early fault identification method in this research. SVM is a machine learning technique for classification and regression. The basic idea of SVM is to map linear inseparable input data into a high dimensional linear separable feature space via a nonlinear mapping technique, and do linear classification or regression in the space. SVM can work well in many learning situations, as this method can generalize to unseen data, adapt to small sample, and is amenable to continuous and adaptive on-line learning[13]. Since the number of samples is relatively low, which makes SVM a more efficient method compared to others, as is summarized by Yang et al.[14] and Yuan et al.[15].



(a) Definition of closeness; (b) Definition of abundance.

Fig. 1. Definition of closeness and abundance

The approaches to obtain the features and identify early fault can be summarized as a flowchart illustrated in Fig.2.

First, horizontal and vertical displacement of shaft is collected using displacement sensors. Then shaft orbit could be obtained. In the following step, closeness and abundance could be calculated as shaft orbit feature.

In the other hand, vibration signal is collected using vibrating sensor. In the following step energy features with 32 dimensionalities are extracted using WPT method and then dimensionality reduction is carried out using PCA method. Thus energy features with 2 dimensionalities are obtained as contrast.

At last, SVM method is implemented to identify the different stages of rotor unbalance. Shaft orbit features and energy feature are used separately in identification so that the result could be compared and the effectiveness of shaft orbit features could be verified.

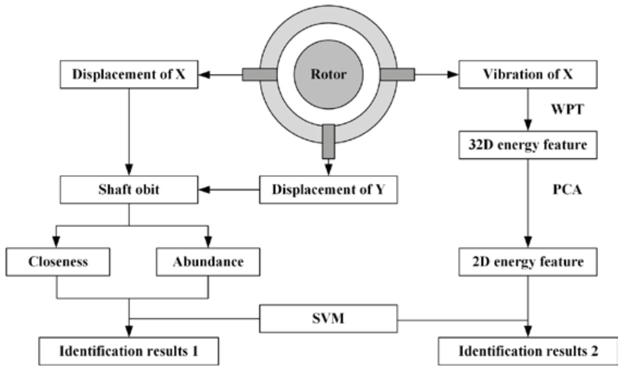


Fig. 2. Flowchart of feature extraction and early fault identification

3. Experiments and results

3.1. Experiments and data description

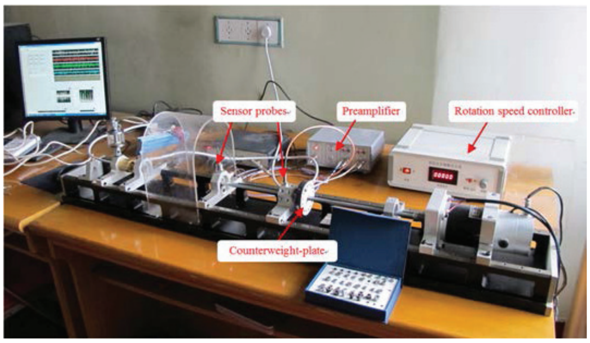


Fig.3. Diagram of experimental setup

Data used in this paper come from a series of experiments on Bently rotor testbed as is shown in Fig.3. A counterweight-plate is fixed in the middle of the rotor, on which screws with different weight can be screwed during the rotor unbalanced experiments in order to simulate different status of the unbalance fault evolving process.

There are four loading conditions: none mass, 0.4g, 3.6g and 5.5g, corresponding to normal operating condition, early fault operating condition, moderate fault operating condition and severe fault operating condition. The rotation speed is controlled at 2400 rpm. Data are probed by vibration sensors and displacement sensors and the sampling frequency is 1000Hz. 50 groups of data sets are obtained under each of the four conditions above.

3.2. Feature extraction

Closeness and abundance are calculated and formed a 2*4*50(number of features*number of loading conditions*number of samples) shaft orbit feature matrix. Energy features of frequency spectrum are also extracted and formed a feature matrix with the same dimensionality.

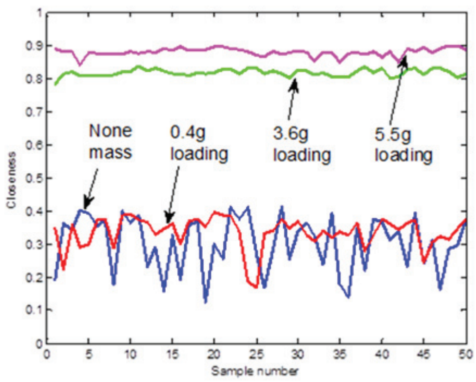


Fig.4. Closeness under the four conditions

The closeness and abundance under the four conditions are shown in Fig.4 and Fig.5 respectively. The energy features of one group of samples before dimension reduction is shown in Fig.6.

It is obvious that both closeness and abundance varied a lot when loading mass changed, especially between none mass and 0.4g loading mass, while the change between 3.6g and 5.5g loading mass is relatively unconspicuous.

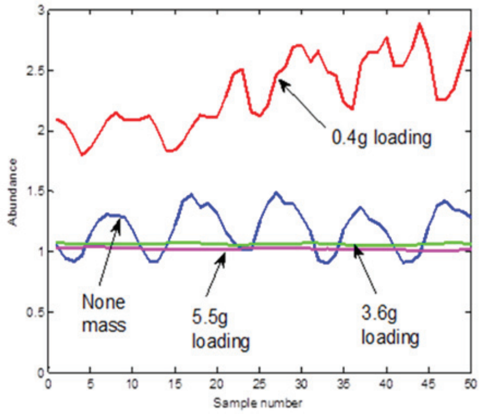


Fig.5. Abundance under the four conditions

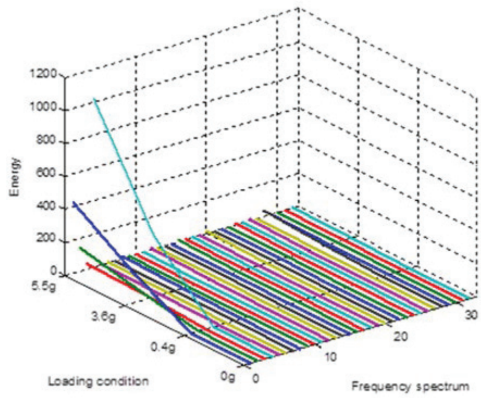


Fig.6. 32D energy features extracted using WPT

3.3. SVM based early fault identification and results

The identification process focus on classifying early fault condition (loaded with 0.4g) from all the other conditions. The feature samples are divided into different number of training samples and testing samples, as is shown in the first vertical lines of Table 1 and Table 2.

Elapsed time for training and testing is also shown in the two tables. The accuracy rates of early rotor unbalanced fault identification utilizing the energy features and the shaft orbit features are shown in the last vertical lines of Table 1 and Table 2 respectively.

Table 1: Early fault identification results using the energy features

Sample number (Training /testing)	Training time (s)	Testing time (s)	accuracy rate (%)
40/160	0.1629	0.0154	77
80/120	1.8113	0.0191	77.5
100/100	10.7827	0.0277	77
120/80	11.0838	0.0250	72.5
160/40	15.6122	0.0313	77.5

Table 2: Early fault identification results using the shaft orbit features

Sample number (Training /testing)	Training time (s)	Testing time (s)	accuracy rate (%)
40/160	0.2581	0.0100	92.5
80/120	1.3184	0.0166	95
100/100	2.7307	0.0167	100
120/80	4.4321	0.0182	100
160/40	15.9418	0.0184	100

3.4. Discussion

It is obvious from the aforementioned results that the features extracted from shaft orbit have better performance in identifying early rotor unbalanced fault, which is of great significance in prognosis of rotating machinery. Since the shaft orbit could provide sufficient fault information to identify the commencement of rotor unbalanced fault, the potential of utilizing shaft orbit as a new feature source for rotating machinery prognosis to provide more early fault information, so that identification and classification of early fault for rotating machinery would become easier to realize, will be notable.

4. Conclusion

It can be concluded from the research that shaft orbit is a promising feature source for rotating machinery prognosis. Feature extracted from the shaft orbit is not only effective in failure classification, which is proved and commonly accepted in traditional rotating machinery diagnosis, but also feasible to identification of early fault during the evolving process of fault in rotating machinery, which indicates that shaft orbit has the potential for providing abundant fault information in rotating machinery prognosis.

Acknowledgements

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